



Nothing can compare with a population, besides agents

Yann Busnel

► To cite this version:

Yann Busnel. Nothing can compare with a population, besides agents. 21th IEEE International Conference on Telecommunications (ICT 2014), May 2014, Lisboa, Portugal. 8 p. hal-00998700

HAL Id: hal-00998700

<https://hal.science/hal-00998700>

Submitted on 2 Jun 2014

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Nothing Can Compare with a Population, Besides Agents

Yann Busnel

LINA / Université de Nantes
2, rue de la Houssinière – BP 92208
44322 Nantes Cedex 03 – FRANCE
Email: Yann.Busnel@univ-nantes.fr

Abstract—Leveraging the resemblances between two areas explored so far independently enables to provide a theoretical framework for distributed systems where global behaviors emerge from a set of local interactions. The contribution of this paper arise from the observation that population protocols and multi-agent systems (MAS) bear many resemblances. Particularly, some subclasses of MAS seem to fit the same computational power than population protocols. Population protocols provide theoretical foundations for mobile tiny device networks. On the other hand, from long-standing research study in distributed artificial intelligence, MAS forms an interesting model for society and owns a broad spectrum of application field, from simple reactive system to social sciences. Linking the both model should offers several extremely interesting outcomes.

I. INTRODUCTION

With the recent expansion of distributed system the two last decades, a boundless set of models has been developed to capture diversity and richness of these systems. Among this set, some models, while proposed in different context, catch the same range of computability. Some recent studies deal with the comparison and equivalence between models [1], [2], [3], [4], [5]. In this paper, we investigate the connections between two famous models: Population Protocols and Multi-Agent Systems (MAS).

Population protocols [6] provide theoretical foundations for distributed systems in which global behavior emerges from a set of simple interactions between their agents. Originally developed in the context of mobile tiny devices, typically sensors, in this model, agents are considered anonymous, and therefore, undistinguishable. Many variants of population protocols have been proposed [7], [8], [9]. Among them, community protocols [10] augment the original model by assigning agents a unique identifier and letting nodes remember a limited number of other identifiers. This not only significantly increases the computation power of the system but also provides a way to tolerate a bounded number of byzantine failures. In the sequel, the class of population protocols and variants will be referred as *population protocols*, and the original model as *basic population protocol*.

More specifically, the population protocol model consists in a finite space of agent's states, a finite set of inputs, a finite set of outputs and a transition function. The set of possible node's interactions is represented by a graph. When two agents are sufficiently close for a sufficiently long time, they interact by exchanging their local information, and update their state according to the transition function. For instance, if agents

are small devices embedded on animals, an interaction takes place each time two animals are in the same radio range. The interaction patterns, orchestrated by a scheduler, are considered as unpredictable. Yet, the scheduler is assumed to be *fair i.e.*, it ensures that any reachable global system state can be reached infinitely often. In the absence of global knowledge, agents cannot usually verify that the protocol has terminated, therefore the model considers convergence (of the distributed output) rather than termination.

On the other hand, largely inspired by the social behavior analysis of insect colony, Multi-Agent System model aims at studying the concept of collective and/or distributed intelligence [11]. The former model and its several extensions should be viewed as a crossroads in artificial intelligence (AI), distributed AI, distributed systems, software engineering, and smart objects.

As proposed in [11] and enhanced in [12], a MAS is made up of an environment, wherein a set of active objects, so called agents, interact with passive objects. A set of relation links objects between them, according to their activity, as a set of operations defines what is possible to apply to objects. Finally, some operators are in charge to reflect the operation mapping on the environment (usually denoted “universe laws”). It exists a specific case where the environment is empty and its does not exists passive object. This kind of system is called *purely communicating MAS*, as the set of relations defines a network between agents, for which actions are reduced to communication. This specific structure is commonly used in distributed AI, mostly for collaboration between units design for problem solving of expert systems.

Usually, MAS are studied owing to their noteworthy ability for self-organization, and are sometimes surprisingly able to reproduce certain form of complex social systems. MAS could be split in two main classes: Cognitive and Reactive agents. These classes come from the design of the active agents, according to their algorithmic ability. More precisely, the cognitive class is commonly used for distributed AI as the reactive one permits to study virtual life [13]. In this paper, we mostly consider the latter one that shares several similarities with the Population Protocol model. Recent interest in the probabilistic convergence of MAS raises [14], [15]. A motivation of our work relies on the fact that the latter convergence has been extensively studied in the Population Protocol model [7], [8], and results should be simply bring into some MAS models.

As in [2] in which authors bridge the gap between population protocols and gossip-based protocols, the aim of this paper is then to correlate the two aforementioned model: Population Protocols and Multi (reactive) Agents Systems, and more specifically, the ones made up of *eco-agents*. They both rely on finite-state agents. Both aim at achieving an emerging global behavior from a set of local interactions in a fully decentralized manner. The main contribution of this paper is to acknowledge these similarities and leverage them in both contexts.

This paper is organized as follow. In Section II, we present a classification of Multi-Agent Systems. Second, Section III provides some background on basic population and community protocols. Then, we prove their equivalence in Section IV and discuss some opportunities of leveraging it, before concluding in Section V.

II. DIFFERENT KINDS OF AGENT

The *Kenetic* [11] claims to be the science and technics of artificial organizations. Using MAS as a designing tool, this field of research possesses the global control of all the experimental system parameters as an advantage. Yet, if the designer is able to tune any possible parameters, she has no access to any determinism aspect, regarding the system evolution. Quite the contrary, as changing configuration in MAS are subject to chaotic phenomena. This implies that any variation in initial parameter, or any adding of insignificant random variable, should lead the same system to exactly opposite final state. In fact, these tiny changes are dramatically magnified through interactions between agents, avoiding some precise system state prediction.

All the Kenetic problems are located at a meeting point of the notion of agent and of society. In other words, it is at a crossroads in the relationship between individual behavior and globally observed phenomena. In this context, cooperation, conflict, collaboration and coordination of actions make sense. Let us restrain the possible field by defining what we mean by *agent* and multi-agent system.

A. MAS Model

MAS are not yet subject to any law. Any work in this model is located in the center of a duality: Agent and Organization. Any organization comes from agent's interactions, but the local behavior of these agents should be modified in return from the constraints imposed by the created organization structures. Except predefined organizations by designers, task coordination, assignment and distribution are resulted from agents themselves. Some emerging properties appear, without any initial programming. It is necessary to introduce two schools of thought according to the model appliance, mainly relying on architectural differences; these differences concern the algorithmic nature of used agents. One school of thought is specialized in distributed AI, so called *cognitive school*, as the other one, denoted *reactive school*, is more interested in virtual life. The one considered in this paper corresponds to this reactive one.

1) *Cognitive agents*: Cognitive MAS design aims to reach communication and cooperation in classical expert systems. In this case, the MAS will be made up of a small number of

"intelligent" agents. Each one owns a basic knowledge that includes a set of mandatory information and technical know-how in order to succeed in its task, and to manage interactions with its environment and other agents. They are sometimes called *intended*, i.e., they own some goals, and explicit plans permitting to reach them. In the context of cognition, mostly planned, MAS leads to some group of individuals, govern by predefined social rules (for instance, in case of conflict, agents should be forced to negotiate). Researches in this field often rely on sociological studies about organization and small groups. In this paper, we do not consider further this kind of MAS.

2) *Reactive Agents*: The main class considered in this paper relies on the fact that a globally intelligent system should not required individual intelligence of its agents. Simple reaction mechanism to stimuli should resolve complex problem, without short-term plan, or explanation of aims and objectives. These MAS permit to raise some self-organization, as the famous example of ant's colony. In the latter, as all ants are undistinguishable, and without any global authority, coordination raised from agents' action in order to develop and save the colony. This collective entity is able to resolve complex issues as construct the anthill, find food, take care of eggs and larva, etc. [16]. Emerging organization is principally related to reactive MAS, as they are not characterized by predefined structures (which is seldom, if ever, the case of cognitive MAS).

B. Formalism

1) *Multi-Agent System*: We propose to model a MAS as proposed in [11].

Definition 1: A *Multi-Agent System* (MAS) is a system made up of: (i) An environment E , i.e., generally a metric space; (ii) A set of objects O , which are associated with a position in E . Most of these objects are *passive*, i.e., they can be sensed, created, removed or modified by agents; (iii) A set of agents A such that $A \subseteq O$, which represent *active* entities of the system; (iv) A set of relations R that links objects (and thus agents) between them; (v) A set of operations Op that lets agents in A to perceive, produce, consume transform and manipulate objects in O . (vi) Operators responsible for applying these operations and the environment reaction to this modification. We denote these reactions *Universe Laws*.

It exists a specific case of MAS where $A = O$ (i.e., there is no passive objects) and where $E = \emptyset$. This kind of system is call *purely communicating MAS*, as the set of relations R defines a network between agents, for which actions are reduced to communication. This specific structure is commonly used in distributed AI, mostly for collaboration between units and designed for problem solving of expert system. This organization emulates the modus operandi of a social structure as administration for instance.

Computational power of specific MAS relies on the potential of the environment [17]. The environment gives structure to the MAS, by providing a kind of shared memory, or a physical/spatial structure. In this study, we mainly focus on virtual environment using discrete representation. The environment could also abstract the communication structure, which is composed by an infrastructure for message passing, stigmergy

or implicit communication. In cognitive MAS, it should also provide some social structure, defining roles, groups and communities of agents. We introduced then the notion of *autonomous environment*. An autonomous environment is defined as an environment with extended functionality compared with a simple spatial structure. The simplest way to model the environment is to provide only a metric space in order to estimate the ability of communication of any two agents, according to their distance between their respective locations. Any enhanced environment will be denoted as autonomous in the following.

2) *Agent*: The core entity of MAS is the agent itself. As introduced in Section II-A, agents should be cognitive or reactive. However, this classification is sometimes too simplistic. We need to enhance it according to two axes:

— Agent's comportments are usually leaded by their teleonomic behavior¹ in contrast with the reflex infers by perception. The trends that govern agents should come either from the environment, or explicitly expressed in agents. We mention it as a *reflex* behavior in the first case, and a *teleonomic* one in the second one.

— Agent's relation with the environment raises the classical problem of subject/object. Is an agent have an explicit and symbolic representation of the surrounding world, on which she is able to reason or this representation is sub-symbolic, *i.e.*, integrated in its sensorimotor intelligence. In the first case, we mention *cognitive* agent, and in the second, *reactive* agents.

C. Eco Problem Solving

The **Eco Problem Solving (EPS)** is a decentralized approach of problem solving, using emergence of interacting reactive agents [18]. A stable state is then sought and considered as the solution of the problem.

Any eco-agent has only one purpose: to be satisfied. Its environment is composed by the other neighboring agents. The latter agents should be in an acquaintance or in a dependency network, interacting using perception of actions. Two specific perceptions of eco-agent exist: being aggressed and being hampered. Three different actions can then be chosen: reach satisfaction (carrying the action that reach its objective), aggress another agent, or take flight. It can be represented as a finite state automaton, with four-internal state: Satisfied (*S*), Seeking satisfaction (*SS* – usually the entry state), Seeking to take flight (*ST*) and Taking flight (*TF*). A transition relation is then set between these states. The actions made by an agent in its acquaintance or its dependency network follow the rules hereafter:

- if an agent is satisfied, it informs his dependencies that they should be satisfied also;
- if an agent cannot be satisfied yet, it seeks the hampering agents among its acquaintance and aggresses them;
- if an agent seeks to take flight, it seeks the hampering agents among its acquaintance and aggresses them.

EPS can be applied in very different context [18], from task scheduling (using "task agents" and "resources agents"), to production line optimization, including simulation of emergent structural turbulence stability in fluid dynamics. Depending on

the applicative requirement, eco-agent should own an identifier or not. The latter case infers a specific class of EPS so-called *Anonymous EPS* in the rest of this paper.

However, the scope of possibilities of eco-agent is not restricted to problem solving. It is especially adapted to evolving universe simulation. In fact, in an eco-agent system, an external stimuli is treated as any other entry of the problem. Any agent acts locally in response of a perturbation. It is perfectly illustrated by the *Misachieving baby* problem [19]. It introduces some malicious external adversaries, which are very powerful and raise the difficulty of eco-resolution.

III. ABOUT POPULATION PROTOCOLS

In this section, we briefly present the basic population protocol model and the community protocol variant, which relaxes the assumption on the anonymity of agents.

A. Basic population protocol

The basic population protocol model, initially introduced in [6], is composed of a collection of agents, interacting pairwise in an order determined by a fair scheduler. Each agent has an input value and is represented by a finite state machine. This agent can only update its state through an interaction. Updates are defined by a transition function that describes the function f computed by the system. At each interaction, the agents compute an output value from their current state and converge eventually to the correct output value, depending to the inputs initially spread to the agents.

More formally, a population protocol is composed of: (i) a complete interaction graph Λ linking a set of n agents; (ii) a finite input alphabet Σ ; (iii) a finite output alphabet Y ; (iv) a finite set of possible agent's states Q ; (v) an input function $\iota : \Sigma \rightarrow Q$ mapping inputs to states; (vi) an output function $\omega : Q \rightarrow Y$ mapping states to outputs; (vii) a transition relation $\delta : Q \times Q \rightarrow Q \times Q$ on pairs of states.

In the sequel, we call $(p, q) \mapsto (p', q')$ or (p, q, p', q') a transition if $(p, q, p', q') \in \delta$. A transition can occur between two agents' states only if these two agents have an interaction. The protocol is deterministic if δ is a function (*i.e.*, at most one possible transition for each pair in Q^2). A configuration of the system corresponds to an unordered multi-set, containing states of all agents. We denote $C \rightarrow C'$ the fact that a configuration C' can be obtained from C in one step (*i.e.*, with only one transition for one existing interaction). An execution of the protocol is a finite or infinite sequence of population configurations C_0, C_1, C_2, \dots such that $\forall i, C_i \rightarrow C_{i+1}$. As introduced above, the order of the interactions is unpredictable, and is decided by the scheduler. The scheduler is assumed to be *fair*, *i.e.* a feasible configuration cannot be endlessly ignored. In other words, if a configuration C appears an infinite number of times during an execution, and there exists a possible step $C \rightarrow C'$, then C' must also appear an infinite number of times in the execution. This ensures that any attainable configuration is eventually reached.

B. Community protocols

Many variants of the last model exist. In this paper, we focus on the specific extension so-called community protocol [10], which significantly increases the computational power

¹"Teleonomy" represents the scientific concept of end in itself (purposefulness and goal-directedness of structures and functions in living organisms).

of the basic population protocol. This model augments the basic population protocol model by assigning unique identifiers to agents. All possible identifiers and a special symbol \perp are grouped in an infinite set U . The difference between basic population protocols and community protocols is the definition of the set of states: $Q = B \times U^d$ where B is the initial definition of the population protocol's set of states collapsed to a memory of d identifiers. As in population protocols, algorithms cannot use any bound on the number of agents and moreover, U is infinite. In order to maintain the population protocol spirit in this extended model, some constraints are added: only existing agent identifiers can be stored in the d slots intended for identifiers of an agent's state and no other structural information about identifiers can be used by algorithms. We consider, for $q \in Q$ and $id \in U$, that $id \in q$ means that q stores id in one of its d identifier slots. Thus, community protocols have to verify the two following formal constraints: $\forall(q_1, q_2, q'_1, q'_2) \in \delta$,

$$id \in q'_1 \vee id \in q'_2 \Rightarrow id \in q_1 \vee id \in q_2. \quad (1)$$

Consider π a permutation of U with $\pi(\perp) = \perp$. For $q = \langle b, u_1, u_2, \dots, u_d \rangle \in Q$, let $\hat{\pi}(q) = \langle b, \pi(u_1), \pi(u_2), \dots, \pi(u_d) \rangle$. We assume that:

$$\forall(q_1, q_2, q'_1, q'_2) \in \delta : (\hat{\pi}(q_1), \hat{\pi}(q_2), \hat{\pi}(q'_1), \hat{\pi}(q'_2)) \in \delta. \quad (2)$$

In short, the first assumption ensures that no transition introduce new identifiers and the second one that identifiers can only be stored or compared for equality, but not manipulated in any other way. Any population protocol can be viewed as a community protocol with $d = 0$.

IV. POPULATION PROTOCOLS vs. REACTIVE AGENTS

Recently, the probabilistic convergence of MAS has been studied apart [14], [15]. A motivation of our work relies on the fact that the latter convergence has yet been extensively studied in the Population Protocol model [7], [8], and these results should be simply bring from one model to another.

In this section, we prove the classification and the relations between all the considered models that are summarized in Figure 1 where R-MAS-AE (resp. R-MAS-NAE) means Reactive MAS with Autonomous Environment (resp. without Autonomous Environment). This provides a refined classification of MAS and population protocols. Let us split the proof in three main theorems.

First of all, the two left horizontal relations of Figure 1 are straightforward by extension of [2], as they are based on the fact that increasing the model with unique agent identifier allows to extend the computational power of the former model. Thus, we obtain that Anonymous-EPS \prec EPS and PP \prec CP. On the other hand, the rightest vertical relation between R-MASs is also straightforward as an autonomous environment can obviously simulated a non-autonomous environment, using a restriction on the environment of the R-MAS-AE. The reverse side is impossible as agents in R-MAS-NAE are not able to deterministically compute the unique evolution of their environment. Thus, we trivially obtain that R-MAS-NAE \prec R-MAS-AE. In the following sections, we provide proofs of remaining relations illustrated on Figure 1.

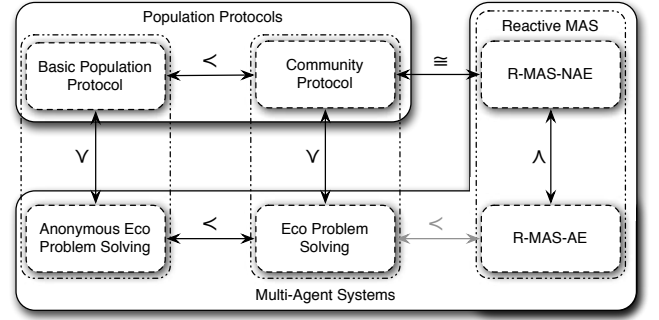


Fig. 1. Relationship between Multi-Agent Systems and Population Protocols

A. Anonymous EPS weaker than Basic Population Protocol

We show there that there exists a population protocol \mathcal{P} able to simulate any execution of eco-resolution.

Theorem 1: If f is computable by a protocol from Anonymous EPS, then there exists a basic population protocol which can compute f .

Proof: Let \mathcal{E} an EPS using eco-agents that computes a specific function f . As presented above, a finite-state machine models eco-agents.

Mapping the domain of the transition function: The domain of any relation in R or operation in Op is finite (and corresponds to some Cartesian products of O , the set of objects, with \mathcal{D}_S the set of possible states of an object in the environment). Moreover, as elements in $R \cup Op$ are functions, their ranges are also finite by definition. Based on these sets, we define $\mathcal{D}_{\mathcal{E}}(g)$ a specific subset of the Cartesian product between the domain and the codomain of $g \in R \cup Op$ (i.e., $\mathcal{D}_{\mathcal{E}}(g)$ contains each ordered pair such that the first entry is in the domain of g and the second entry is the mapped element of this first entry by g). Thus, for any $g \in R \cup Op$, $\mathcal{D}_{\mathcal{E}}(g)$ is finite and contains all the possible transitions of object states, based on the knowledge of a surrounding object sub-state in the environment.

Design of the basic population protocol for the purpose of simulation: Consider the following basic population protocol \mathcal{P} , represented by the 7-uplet $(\Lambda, \Sigma, Y, Q, \iota, \omega, \delta)$. Consider a complete interaction graph Λ . Let the set of agent states in \mathcal{P} be identical to the set of object states, i.e., $Q = \mathcal{D}_S$. Consider that Σ and Y are the same as the input and output sets of \mathcal{E} , if they exist. In this case, ι and ω are the same functions than the ones which respectively associate the input set of \mathcal{E} to \mathcal{D}_S , and \mathcal{D}_S to the output set of \mathcal{E} . Conversely, if no specific input and output sets are defined in \mathcal{E} , then $\Sigma = Y = \mathcal{D}_S$ and $\iota \equiv \omega$ corresponds to the identity function. Finally, the transition function δ is defined as follows.

$$\forall g \in R \cup Op, \forall (s_l, s_r, s'_l) \in \mathcal{D}_{\mathcal{E}}(g),$$

$$\exists (s_r, s_l, s'_r) \in \mathcal{D}_{\mathcal{E}}(g) \text{ s.t. } (s_l, s_r, s'_l, s'_r) \in \delta.$$

On the environment and the fair scheduler: Communication exchange between agents is an inherent characteristic of EPS. However, in this class, the environment is only used to model the ability for two agents, or an agent and an object, to pairwise interact. Therefore, as the scheduler of \mathcal{P} is mandatory fair, any possible interaction eventually happens and makes

sufficient condition to obtain a correct execution of \mathcal{E} , using the aforementioned \mathcal{P} .

Thus, there exists a basic \mathcal{P} , which simulates the considered EPS \mathcal{E} and computes the function f . Then, for any function computable by an EPS, there exists a basic population protocol, which stably computes this function. ■

On the other hand, the reverse of Theorem 1 is not valid. In fact, there exists some functions that are computable by a population protocol, but no anonymous EPS is able to compute the same function. This is mainly due to the global fairness property associated to the Population Protocol model. In some EPS, it is possible to construct a loop-based infinite execution that endlessly avoid a given reachable system state, belying the aforementioned fairness property.

B. EPS weaker than Community Protocol

Along the same lines, we prove here the following theorem in order to prove that it is possible to simulate any EPS using a community protocol.

Theorem 2: If f is computable by a protocol from EPS, then there exists a community protocol which can compute f .

Proof: Due to space constraints, we are not able to provide the complete proof. The interested reader is invited to look at the companion paper [20]. ■

Again, the opposite of Theorem 2 cannot be verified, due to the same argument about the fairness property (see Section IV-A).

C. R-MAS-NAE is equivalent to Community Protocol

Finally, we prove here the following theorem in order to prove the equivalence between community protocols and R-MAS-NAE.

Theorem 3: A predicate is computable by a community protocol if and only if it can be computed by a Reactive MAS without Autonomous Environment (R-MAS-NAE).

Proof: The proof of Theorem 3 is obtained by showing respectively both implications of the equivalence. Based on the usage of the environment as the scheduler, it is almost straightforward to prove the first implication that is, for each f computable by a community protocol, there exists a R-MAS-NAE which compute f . On the opposite, we argue that, for each f computable by a R-MAS-NAE, there exists a community protocol which computes f . Due to space constraints, we are not able to provide the complete proof. The interested reader is invited to look at the companion paper [20]. ■

V. CONCLUSION AND FUTURE WORKS

The main contribution of this paper is to establish a correlation between Population Protocols and Multi (reactive) Agents Systems. Both aim at achieving an emerging global behavior from a set of local interactions in a fully decentralized manner. This parallel between two worlds, explored so far independently, offers several extremely interesting outcomes, acknowledge these similarities and leverage them in both contexts. These results can be leveraged for existing results as well as results to come in both areas. For instance, the

intensive research around structured language for MAS (as KQML or FIPA ACL for instance) should be mapped to the population theory. That should lead to a standardization of high-level communication between agents. From the inverse, the theoretical analysis of Population Protocols models could resolve the issue of a lack of computational power analysis with different MAS models.

Acknowledgment. The author would like to warmly thank Philippe Lamarre (INSA Lyon, France) for his valuable discussions at the early steps of this work.

REFERENCES

- [1] A. Basu, B. Bonakdarpour, M. Bozga, and J. Sifakis, "Systematic correct construction of self-stabilizing systems: a case study," in *intl conf. on Stabiliz., safety, and security of dist. syst. (SSS '10)*, 2010.
- [2] M. Bertier, Y. Busnel, and A.-M. Kermarrec, "On gossip and populations," in *Intl Colloquium on Structural Information and Communication Complexity (SIROCCO 2009)*, Piran, Slovenia, May 2009.
- [3] B. Marzougui, K. Hassine, and K. Barkaoui, "A new formalism for modeling a multi agent systems: Agent petri nets," *J. Software Engineering Applications*, vol. 12, no. 3, pp. 1118–1124, december 2010.
- [4] S. Perathoner, E. Wandeler, L. Thiele, A. Hamann, S. Schliecker, R. Henia, R. Racu, R. Ernst, and M. G. Harbour, "Influence of different system abstractions on the performance analysis of distributed real-time systems," in *ACM/IEEE intl conf. on Embedded software (EMSOFT '07)*, 2007.
- [5] S. Poslad, "Specifying protocols for multi-agent systems interaction," *ACM Trans. Autonomous and Adaptive Syst.*, vol. 2, November 2007.
- [6] D. Angluin, J. Aspnes, Z. Diamadi, M. J. Fischer, and R. Peralta, "Computation in networks of passively mobile finite-state sensors," *Distributed Computing*, vol. 18, no. 4, pp. 235–253, mars 2006.
- [7] D. Angluin, J. Aspnes, and D. Eisenstat, "Fast computation by population protocols with a leader," *Distributed Computing (Special Issue: DISC'07)*, vol. 21, no. 2, pp. 183–199, june 2008.
- [8] D. Angluin, J. Aspnes, D. Eisenstat, and E. Ruppert, "The computational power of population protocols," *Distributed Computing (Special Issue: DISC'07)*, vol. 20, no. 4, pp. 279–304, november 2007.
- [9] J. Aspnes and E. Ruppert, "An introduction to population protocols," *Bulletin of the European Association for Theoretical Computer Science, Distributed Computing Column*, vol. 93, pp. 98–117, octobre 2007.
- [10] R. Guerraoui and E. Ruppert, "Names trump malice: Tiny mobile agents can tolerate byzantine failures," in *Intl Colloquium on Automata, Languages and Programming (ICALP '09)*, 2009, pp. 484–495.
- [11] J. Ferber, *Multi-Agent Systems. An Introduction to Distributed Artificial Intelligence*. London, UK: Addison Wesley, 1999.
- [12] K. P. Sycara, "The many faces of agents," *AI Mag.*, pp. 11–12, 1998.
- [13] F. Gechter, V. Chevrier, and F. Charpillat, "A reactive agent-based problem-solving model: Application to localization and tracking," *ACM Trans. Autonom. and Adaptat. Syst.*, vol. 1, pp. 189–222, Dec. 2006.
- [14] S. Martinez, "A convergence result for multiagent systems subject to noise," in *American Control Conference (ACC '09)*, 2009.
- [15] G. Tang and L. Guo, "Convergence of a class of multi-agent systems in probabilistic framework," in *IEEE Conf. on Decision and Control*, 2007.
- [16] A. Drogoul, B. Corbara, and S. Lal, "Manta: New experimental results on the emergence of (artificial) ant societies," in *Artificial Societies: the computer simulation of social life*, 1995.
- [17] D. Weyns, A. Omicini, and J. Odell, "Environment as a first class abstraction in multiagent systems," *Autonomous Agents and Multi-Agent Systems*, vol. 14, no. 1, pp. 5–30, Feb. 2007.
- [18] A. Drogoul and C. Dubreuil, "Eco-problem-solving model: results of the n-puzzle," *ACM SIGOIS Bull.*, vol. 13, no. 3, pp. 15–, Dec. 1992.
- [19] M. Schoppers, "Universal plans for reactive robots in unpredictable environments," pp. 1039–1046, 1987.
- [20] Y. Busnel, "Nothing can compare with a population, besides agents," CNRS / LINA, Tech. Rep. hal-00933010, 2014.